

Influence of Exchange Traded Fund (ETF) Splits on Investor Behavior

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By

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Abstract

Investors do not always behave rationally. Nominal share prices have been found to influence investor behavior and expectations about the future. One way to measure the impact of nominal share prices on investor behavior is through stock splits, as when they occur, underlying fundamentals do not change, only share price changes. Studies show mixed results on the impact of stock splits on liquidity, as measured by daily trading volumes. Additionally, research shows exchange traded funds (ETFs) have high tracking efficiency, as measured by deviation from net asset value (NAV). To expand on current research and determine the impact of splits and reverse splits on the liquidity of ETFs, this paper measures how trading volumes of ETFs change following splits and reverse splits for the years 2010-2016. Further, this paper measures how deviations from NAV and tracking efficiency of ETFs change following splits and reverse splits. The results suggest that following splits, trading volumes of ETFs on average tend to increase, but not at a statistically significant level. Following reverse splits, trading volumes of ETFs on average increase dramatically at a statistically significant level. Deviations from NAV and tracking efficiency of ETFs do not change significantly following either a split or reverse split. Despite an increase in liquidity post-split, the deviations from NAV largely fluctuate randomly, potentially implying the ETFs were priced efficiently prior to the split. However, there is some evidence of increased mispricing in the days surrounding a split, potentially suggesting irrational investor behavior. Based on these results, it is possible that nominal share prices influence investor behavior regarding ETFs. The cause, however, remains unknown. This paper provides insight into investor behavior that may be valuable not only to investors, but also to the companies that manage ETFs.

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Introduction

Introduction to Exchange Traded Funds (ETFs)

An exchange traded fund (ETF) is a security that owns the underlying assets (stocks, bonds, futures, etc.) and divides ownership of those assets into shares. Owners of ETF shares do not directly own the underlying assets of the ETFs. Instead, they own these assets indirectly (“Exchange Traded Fund (ETF)”). From the first ETF formed in 1993, to 102 ETFs available in 2002, to thousands available today (Simpson and “ETF Screener”), ETFs are a relatively new trading tool. ETFs trade like common stock on an exchange, so they can experience intraday price changes and can be bought and sold throughout the day. Because ETFs trade like stocks, they can also undergo share splits and reverse splits.

Introduction to this Research

Investors do not always act rationally. They have the potential to form skewed expectations and not always act in their best interest. For example, nominal share prices influence investor behavior. This makes stock splits an interesting tool to use to test the impact of nominal share price on investor behavior. When a stock split occurs, the underlying asset does not change; only the number of shares changes in accordance with the size of the split, and the share price will adjust accordingly. However, despite the number of shares and share price being the only things that change, investor behavior can change drastically. For instance, it has been shown that investors irrationally view lower priced stocks as having more upside potential than higher priced stocks (Birru & Wang, 2016).

With there being much research focusing on how nominal prices and stock splits influence investor behavior related to stocks, this paper will look at how nominal prices and splits influence investor behavior related to exchange traded funds (ETFs). Research shows differing results of the impact of stock splits on liquidity, and this research will extend that to see

how ETF splits, and therefore nominal price, impact the liquidity of ETFs. Specifically, as a measure of liquidity, this paper will look at how daily trading volumes, measured as number of shares traded, change following an ETF split or reverse split. Then it will measure how ETFs' deviation from net asset value (NAV) changes following an ETF split. Because splits represent only nominal changes in shares outstanding and share price, there should not be any change in split-adjusted trading volumes or premiums to NAV following an ETF split. A change in investor behavior or mispricing that is unrelated to underlying fundamentals signals irrational investor behavior and inefficiencies in the market. If fundamentals do not change, investor behavior and mispricing should not change.

Compared to stocks, ETFs are a much cleaner environment to test split effects on investor behavior, specifically to test for irrationality. When a traditional stock splits, the split can be used by the company to potentially signal new information about its fundamentals, such that the company expects future earnings to be higher. Contrarily, ETF splits are the decision of the ETF, not the stocks held by the ETF, meaning ETF splits cannot be used to signal information about the fundamentals of the stocks held by the ETF. This suggests that the impact of splits on investor behavior may be less noticeable for ETFs than for traditional stocks.

In the remainder of this paper, there will be a literature review, which highlights the most relevant research already done related to this topic. Following the literature review is the hypothesis section, which discusses the main questions this research seeks to answer and the expected results once the analysis is complete. After that section is the methodology and analysis section, which discusses how the necessary data was collected to answer the proposed questions and thoroughly goes over the techniques that were used to analyze the data and evaluate the

hypotheses. Next is the results section, followed by a discussion of the results, their implications, and future research ideas related to this topic.

Literature Review

Stock Splits and Liquidity

There have been mixed results as to the impact of stock splits on liquidity. Some research has provided evidence suggesting there is a decrease in liquidity following a stock split. In one study, Copeland (1979) tested a random sample of 25 companies on the New York Stock Exchange (NYSE), and found that trading volume following a split increased less than proportionally, and that post-split bid-ask spreads increased significantly as a percentage of the value of the stock, implying a decrease in liquidity following a split. Similarly, using stock splits from 2009 to June 2011 on the NYSE, Rudnicki (2012) found that liquidity, as measured by trading volume, worsened following a split, and there was a steady decline in liquidity in the 81-day period following the split. In another study, it was found that following a reverse split, there was a decrease in bid-ask spread and an increase in trading volume, suggesting that reverse splits enhance the liquidity of the stock (Han, 1995). Lamoureux (1987) and Huang and Liano (2015) also found that there was a decrease liquidity following a stock split.

Contrarily, there are numerous papers that suggest that the opposite is true: that stock splits increase the liquidity of the stock. Slonski and Rudnicki (2011) used trading volume to measure liquidity, and found that from 1992-2010 on the Warsaw Stock Exchange, stock splits contributed to an increase in liquidity. Also, Mohanty and Moon (2007) found that average monthly trading volume following stock splits is significantly higher compared to pre-split levels, implying increased liquidity. Increased post-split liquidity may be the result of increased activity by small investors. One study found that the number of small trades increased drastically following a split (Chen & Wu, 2009). Another study found that following the two-for-one split of the Nasdaq-100 Tracking Stock, the frequency, share volume, and dollar volume of small

trades all increased following the split, implying increased liquidity for small traders. However, the same study found an increase in bid-ask spread following the split, implying decreased liquidity for larger traders (Dennis, 2003).

Nominal Price Influence

There is strong evidence that nominal price influences investor behavior and expectations. One theory as to why stock splits occur is they are used by companies as a mechanism to keep share price in a desired target range. Consistent with this theory, researchers found that since the Great Depression, U.S. stock prices have remained relatively constant at around \$35 in nominal terms because of the proactive efforts of firms splitting their stock. As a result, the authors argue that firms are simply following traditions and norms when they use stock splits to keep stock price in the optimal trading range that is appealing to investors, and this cannot be explained by traditional explanations for stock splits, such as signaling theory (Weld et al., 2009).

Despite this, nominal price influences investor behavior. The impact of nominal price is often tested using stock splits. For instance, it has been shown that similarly priced stocks move together. By measuring comovement of stocks before and after a stock split, it was shown that post-split stocks experienced an increase in comovement with low-priced stocks and a decrease in comovement with high-priced stocks. This suggests that investors categorize stocks based on price (Green & Hwang, 2009). Using stock splits, Birru and Wang (2016) show that investors overestimate the upside potential of low-priced stocks relative to high-priced stocks, indicating that investors view low-priced stocks as cheap assets with more room to grow. In a different experiment, researchers found that lower share prices led to higher expected percentage changes in share price. In the same study, the researcher found that participants in the experiment were

more willing to trade (both buy and sell) shares following a stock split, and less likely to do so following a reverse split (Svedsater et al., 2007). Radcliffe and Gillespie (1979) found that, following a reverse split, both dividend and non-dividend paying companies saw their share prices fall relatively, implying a negative reaction by investors to reverse splits. Further, Baker, Greenwood, and Wurgler (2009) used a measurement known as the “Low-Price Premium” to measure investor demand for low-priced stocks. When comparing this demand to stock split activity, the data suggests that firms cater to investor demands by using stock splits and reverse splits to keep share price in a desired range. These studies show that nominal prices do influence investor behavior, and that firms are aware of this and actively manage their share price to cater to investors.

ETF Tracking/Pricing Efficiency

ETFs tend to be priced efficiently and accurately track their underlying assets. If inefficiencies exist, they tend to be small and disappear quickly. Overall, ETFs in the U.S. are the most price efficient. U.S. ETFs have small deviations from the NAV that average 0.15% and disappear within a day, while ETF pricing in other countries, such as India, can be inefficient, with deviations from the NAV averaging 0.52%-1.40% and lasting for 3 days (Tripathi & Garg, 2016). Engle and Sarkar (2006) found that domestic premiums lasted an average of only 10 minutes, while foreign ETF premiums lasted an average of 3 hours, implying domestic ETFs are priced very close to NAV, while foreign ETFs may not be. In this study, the average premium, measured as the difference between the “midquote” (the average between bid and ask prices) and the NAV, in almost all cases was less than 0.05%. Ackert and Tian (2008), similarly, found that ETFs in the U.S. may trade at a slight premium (0.02%) to NAV, while other country ETFs

average a much higher premium to NAV of 0.10%. This suggests that the higher liquidity of U.S. ETFs is associated with a lower premium.

Using a different approach to detect mispricing, Petajisto (2017) compared ETF prices to the current market prices of a peer group of similar funds and found premiums fluctuating between 1% and 2% for ETFs holding international or illiquid securities. Using this new approach, the premiums were lower than when using the popular method of comparing ETF prices to NAV. This study also showed that ETFs holding liquid domestic securities were priced relatively efficiently. Furthermore, another study found that ETFs with higher assets under management and higher trading volumes positively impacted the tracking ability of ETFs, implying larger ETFs are priced more efficiently than smaller ones (Singh & Kaur, 2016).

Hypothesis

To test the impact of nominal ETF price on investor behavior, this paper will look at daily trading volumes of ETFs and premiums to net asset value (NAV) before and after splits and reverse splits occur. Because there is no change in the underlying assets when a split occurs, in theory there should not be any changes in trading activity following a split. The main hypothesis is that trading patterns (split-adjusted trading volumes) of ETFs will not change following a split or reverse split, no matter how the data is sorted.

Additionally, this research will test if a split influences the ETFs' deviation from NAV. One hypothesis is that the magnitude of deviation from NAV should not change following a split or reverse split because there is no change in the underlying asset when a split occurs. Following the same logic, the tracking efficiency of the ETFs should not change following a split.

In sum, as trading volumes and premiums to NAV are measures of liquidity, the hypothesis is these should not change following an ETF split, however they may as it has been shown that nominal prices influence investor behavior. Consistent with this idea, if nominal price and changes in nominal price influence behavior, the effects on volume should be largest for the most extreme split factors. Because the only fundamental that splits potentially affect is liquidity, any change in investor behavior or mispricing that is unrelated to liquidity is a reflection of irrationality.

Methodology and Analysis

Data Collection

The data that was collected included split ratio, split-adjusted daily trading volumes, NAVs, and prices for ETFs that underwent a split or reverse split during the years 2010-2016, traded on a U.S. exchange, and were actively traded as of October 2, 2017. The main source for this data was Bloomberg's equity screening tool, which was used to collect this data for 90 days before and 90 days after the split occurred. Once this data was gathered from Bloomberg, Excel was used to find the deviation from NAV for each ETF and to analyze the data. A summary of the data used to analyze trading volumes can be seen in Table 1 for splits and Table 2 for reverse splits.

Trading Volumes

To measure the change in trading volumes following a split, the first step was to find the average trading volumes pre- and post-split for each time period (1, 2, 3, 4, 5, 10, 15, ..., 90 trading days; with day 1 being the day the split occurred), which would allow for comparison over time and would allow for observation of how long changes persist. Once the average trading volumes were found for each ETF for each time period, the percent change in volume was found for each ETF for each time period. The average post-split volumes were compared to the average pre-split volumes of the same length of time for each ETF (i.e. for the 5-day range, if the split occurred July 1, the percentage difference between average trading volumes in the 5 days before the split and average trading volumes in the 5 days post-split were found). Then, based on the percent change for each ETF, t-tests were conducted at each time frame with a hypothesized mean of 0 at a 95% confidence level to determine if there were statistically significant differences in average post-split volumes for the ETFs as a whole. The data was separated based

on whether a split or reverse split occurred. The data was further sorted in a variety of ways, including by year of the split, split ratio, and day 1 volumes. T-tests were again conducted with a hypothesized mean of 0 at a 95% confidence level to determine if there were statistically significant differences in post-split volumes depending on the characteristic the data was sorted by.

Deviation from NAV

To measure the change in deviation from the NAV (premium to NAV), a similar process as measuring change in trading volume was used. First, the deviation from the NAV, measured as price minus NAV, was found for 90 days pre- and post-split. Unlike the volumes, which for each time period were measured as an average, deviation from NAV was measured at each point in time without averaging over the time horizon (i.e. for the 5 day time period, instead of measuring the average deviation from NAV 5 days prior to the split and 5 days after the split, the deviation on the 5th day pre-split was compared to the deviation on the 5th day post-split). Once the deviations were found, they were converted into percentages of the NAV to find percent deviations from the NAV pre- and post-split. The time periods were the same as with volumes: 1, 2, 3, 4, 5, 10, 15, ..., 90 trading days. This provides information for both short-term and longer-term analysis.

To measure the magnitude of the change in deviation to NAV, the pre-split percent deviation was subtracted from the post-split percent deviation. This post-split minus pre-split percent deviation measures how much of a shift in deviation from NAV occurs. A positive change implies a shift closer to positive infinity, whereas a negative change implies a shift closer to negative infinity. T-tests were conducted for each time period with a hypothesized mean of 0

at a 95% confidence level to determine if there were statistically significant differences in post-split deviations from NAV compared to pre-split. Again, splits and reverse splits were separated.

To measure how the tracking efficiency of the NAV changed following the split, a similar procedure was followed, except the absolute value of the pre-split percent deviation was subtracted from the absolute value of the post-split percent deviation. Using absolute values provides a good way to measure whether post-split deviations became closer to or further from zero, and therefore a good way to measure if the ETF share price became closer to NAV following a split. A positive change implies a shift away from zero, and therefore less efficient tracking. A negative change implies a shift toward zero, and therefore more efficient tracking. T-tests were then conducted to determine whether there were statistically significant differences in tracking efficiency post-split. The hypothesized mean was 0 at a 95% confidence level, with splits and reverse splits being separated.

These tests provided data on how splits and reverse splits influence deviations from NAV, and how long these changes persist.

Results

Trading Volumes

All Splits and Reverse Splits

The primary hypothesis was that split-adjusted trading volumes should remain the same post-split in the short-term and the long-term for both splits and reverse splits. Following both splits and reverse splits, trading volumes increased on average, both in the short-term (the first 5 days following the split) and the long-term (up to 90 days following the split). Following a split, ETFs saw an initial increase in average trading volume, followed by a drop over the next few days, then a rebound in trading volume. In the long-term, on average, splits showed an increase in trading volume. Reverse splits also saw an increase in trading volumes post-split, but in a much more drastic manner. These results show that, on average, ETFs that underwent a split or reverse split saw an increase in trading volume. On the day of the split, ETFs had an increase in trading volume of 13.5% for splits and 141.5% for reverse splits. In the long-run, an increase in volume was also present. For example, on the 60th day post-split, ETFs had an increase in trading volume of 5% for splits and 117.3% for reverse splits. The graphs show more fluctuation in the short-run than the long-run (Figures 1 and 2).

While there appear to be differences in average trading volumes in the short-term and long-term for both splits and reverse splits, for the most part, only reverse splits had statistically significant differences in average trading volumes post-split (see Tables 3 and 4). For splits, with the exception of the fourth day post-split, the percent change in volumes was not statistically significant for any of the time periods. For reverse splits, the percent change in volumes for each time period resulted in a statistically significant difference.

Figure 1

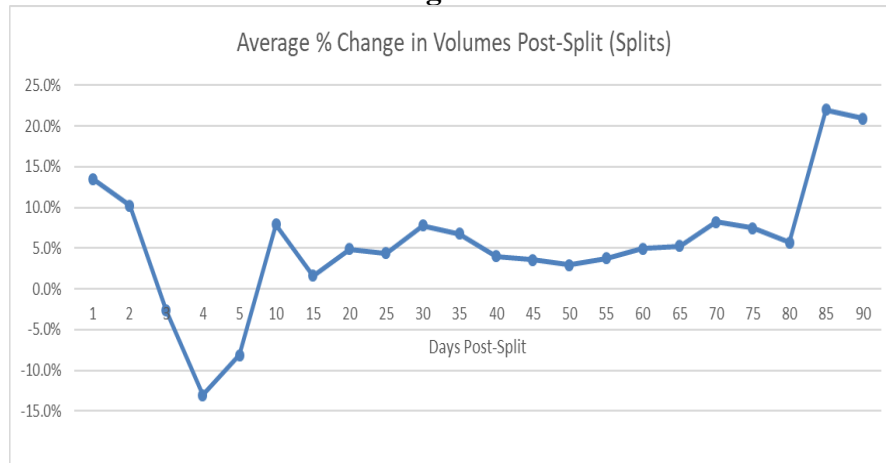
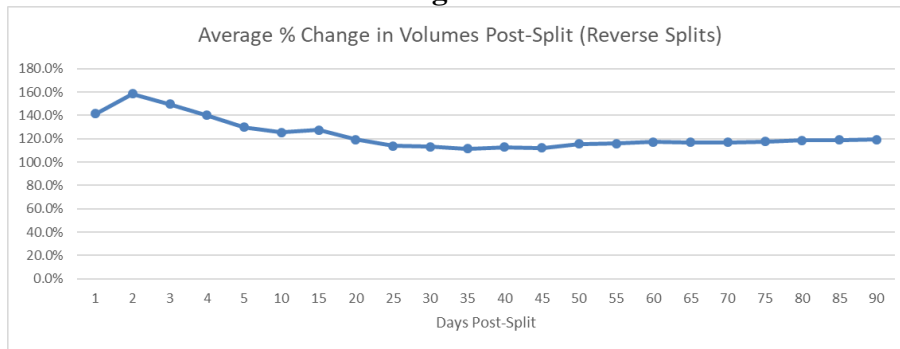


Figure 2



Sorted by Year

Sorting the splits on a yearly basis to see how trading volumes change post-split for the years 2010-2016 shows how the post-split trading volumes change over time. For splits, on average, some years saw increased volume in the short-term and long-term following the split; some saw increased volumes in the short-term and decreased volumes in the long-term; some saw decreased volumes in the short-term and increased volume in the long-term; some saw decreased volume in the short-term and long-term (Figure 3). Contrarily, ETFs undergoing reverse splits, on average, exclusively had increases in trading volumes in both the short-term and long-term (Figure 4). From a statistical standpoint, for splits, post-split volumes mostly were

not significantly different from pre-split volumes (Table 3). For reverse splits, post-split volumes mostly were statistically different from pre-split volumes (Table 4).

Figure 3

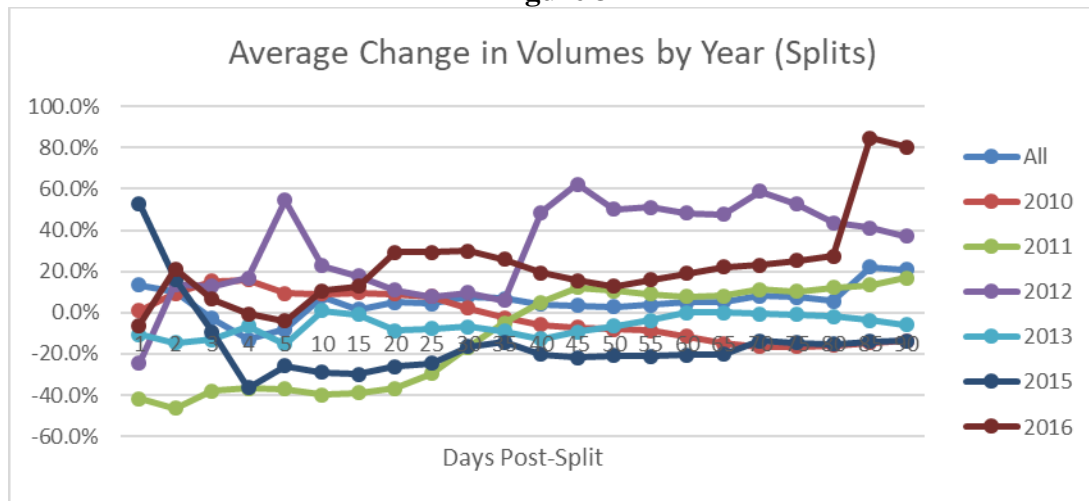
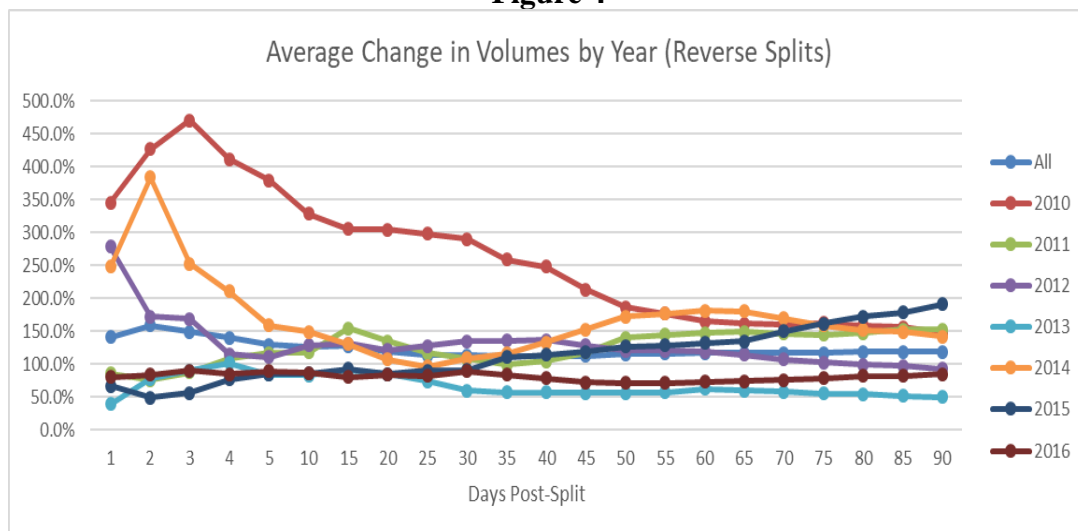


Figure 4



Sorted by Split Ratio

Another factor to take into account is the size of the split, measured by the split ratio. Split ratios above one indicate a split, while split ratios below one indicate a reverse split. For splits, the data was sorted into 3 categories: a split ratio of 2, a split ratio of 3, and a split ratio of 4. Ratios of 2 and 4 behaved similarly, with both starting out with an increase in trading volume,

followed by a decrease in trading volume shortly thereafter, before returning to an increase in volume for the remaining time periods. The split ratio of 3 behaved differently in that it saw a decrease in trading volume following the split, and the decrease persisted through all time periods. The split ratio of 4 saw the biggest changes in volume over the 90 days (Figure 5).

Reverse splits were sorted into 5 groups: split ratio of less than 0.2, split ratio of 0.2, split ratio of 0.25, split ratio of 0.3333, and split ratio of 0.5. All ratios started with and remained at an increase in volumes post-split over all time periods (Figure 6). In the short-term (1 day) and the longer-term (90 days), more drastic split factors saw larger changes in volumes.

Once again, ETFs undergoing a traditional split largely did not see statistically significant differences in trading volume post-split for any ratio. The exception was a ratio of 3, which tested positive for statistical significance in days 1, 2, and 20-55 (Table 3). ETFs undergoing reverse splits largely saw a statistically significant difference in post-split volumes for all split ratios. One exception was a ratio of 0.5, which did not test positive for statistical significance for days 50-90 (Table 4).

Figure 5

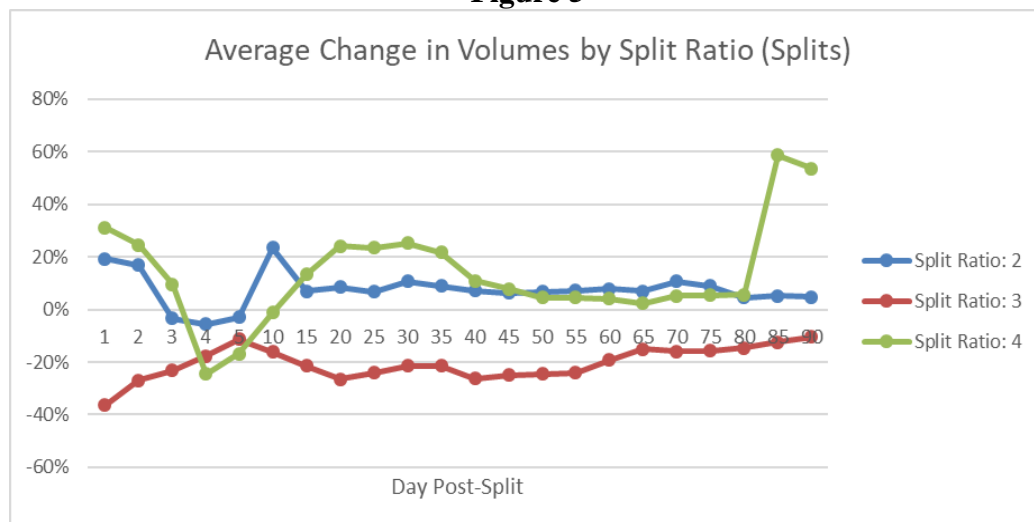
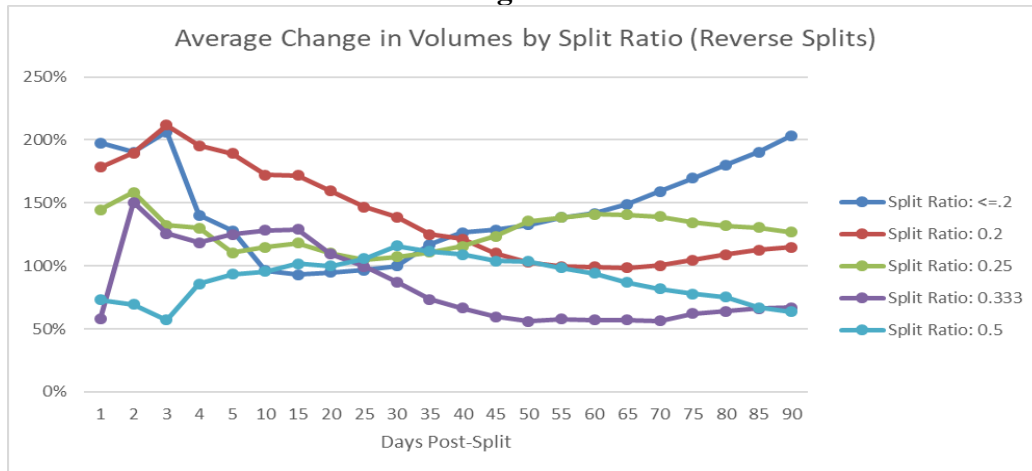


Figure 6



Sorted by Trading Volume on Day 1

To test whether less frequently traded ETFs displayed similar behavior as more frequently traded ETFs, the ETFs were divided into three groups based on their trading volumes on the day of the split. The three groups were (1) ETFs with trading volume greater than 1,000,000, (2) ETFs with trading volume from 100,000-1,000,000, and (3) ETFs with trading volume less than 100,000. For ETFs undergoing a traditional split, group (1) saw an initial decrease in volume, followed by a gradual increase in the long-run. Group (3) initially saw a large increase (Figure 7). For ETFs undergoing a reverse split, all three groups saw large increases in trading volumes following the reverse split (Figure 8). Group (2) tended to see the highest increase, followed by group (1). Group (3) saw the smallest increase in trading volume. Changes in volumes post-split were largely not statistically significant for traditional splits. Group (2) saw a statistically significant difference in trading volumes for the first day post-split, while groups (1) and (3) saw statistically significant differences in days 5 and 4, respectively (Table 3). Reverse splits unanimously saw statistically significant differences in post-split volumes for all groups and all time periods (Table 4).

Figure 7

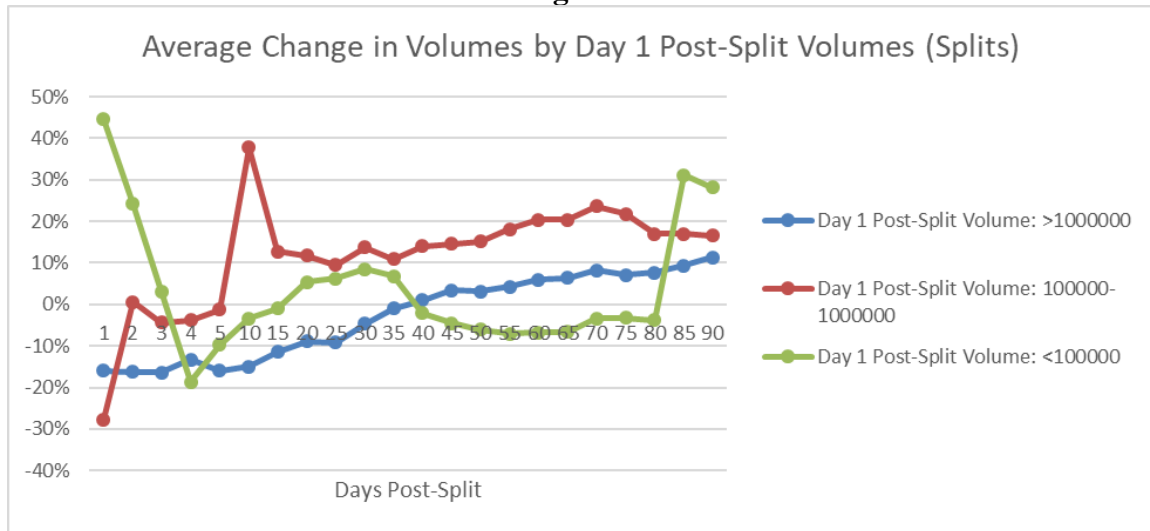
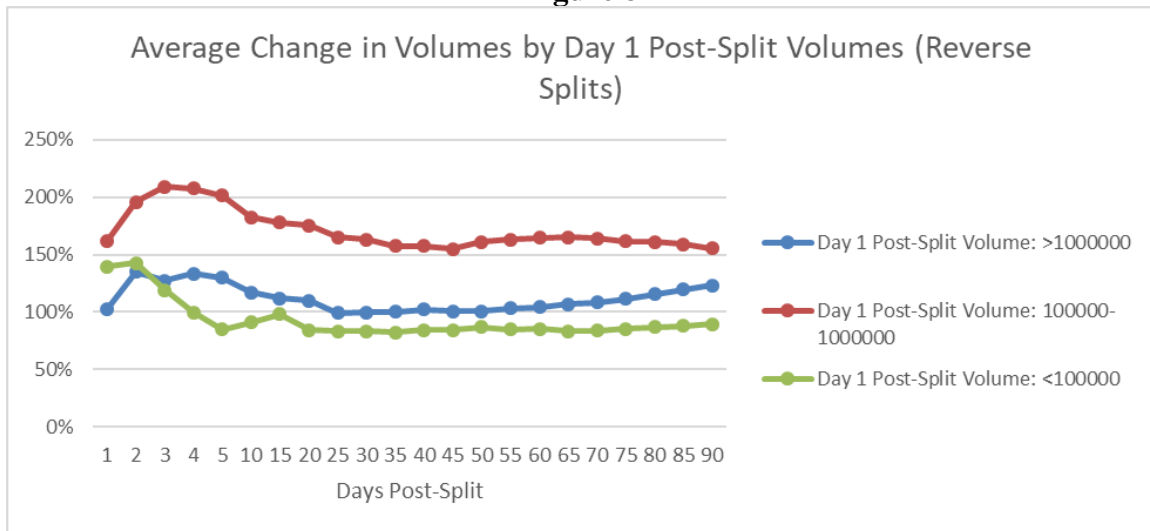


Figure 8



Deviation from NAV

Magnitude of Change

At the end of the day the split occurred (day 1), the deviation from NAV increased by an average of 0.202% (measured as a percent of NAV) for splits and decreased by an average of 0.113% for reverse splits. Comparing the post-split deviation on the second day following the split to the pre-split deviation on the second day prior to the split resulted in a decrease in deviation from NAV by 0.001% for splits and an increase of 0.074% for reverse splits. Figures 9

and 10 provide further results for each time period. Unlike trading volumes, from a statistical standpoint, both splits and reverse splits behaved alike and did not result in statistically significant differences in deviations from NAV post-split (Table 5). Figures 11 and 12 depict the deviation from NAV in the 90 days leading up to and the 90 days following the splits and reverse splits. Unlike when measuring volumes, deviations were not measured using the average over the time period. For example, for the deviation 50 days post-split, the measure provided is the deviation on the 50th day post-split, not the average deviation over the 50 days post-split. As seen in Figure 11, magnitude of deviation from NAV peaked on the day of the event for ETFs that underwent a split.

Figure 9

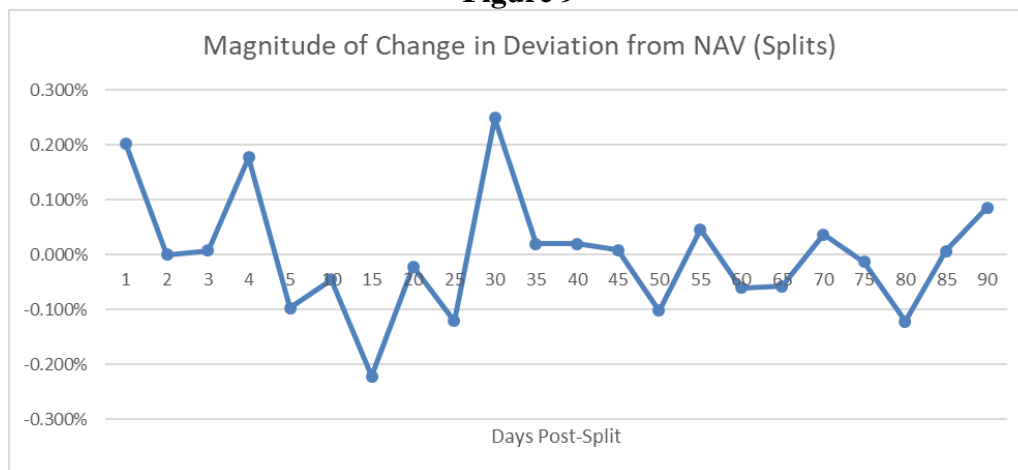


Figure 10

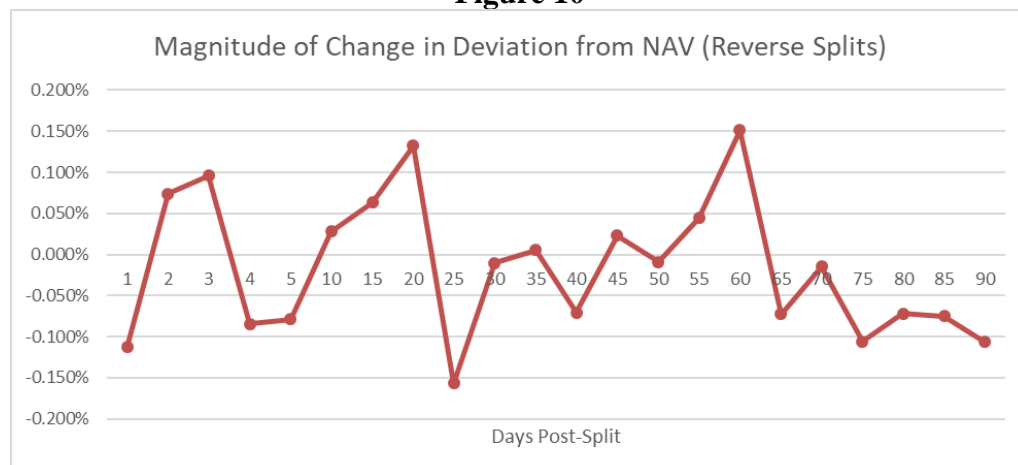


Figure 11

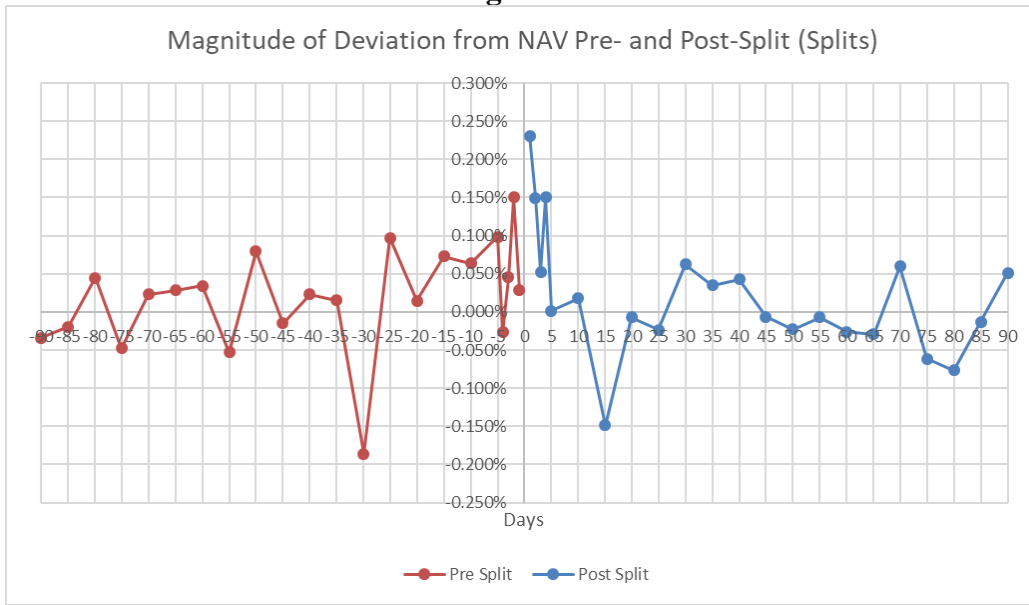
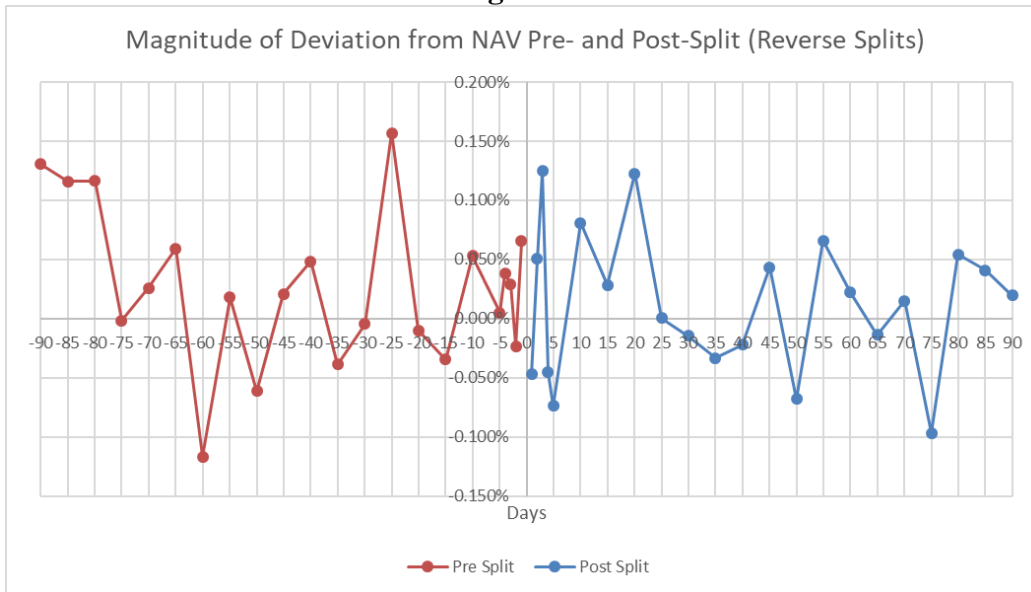


Figure 12



Change in Tracking Efficiency as Measured by Absolute Value of Deviation from NAV

While the magnitude of the change in deviation from NAV post-split shown above measures which direction the NAV moves (up or down), it does not necessarily track if the deviation from NAV gets closer to or further from zero following the split. By finding the absolute values of pre-split and post-split deviations from NAV, it was possible to determine

how much closer to or further from zero deviation from NAV became post-split, and thus how much more or less efficient the actual prices of the ETFs were at tracking the NAVs (Figures 13 and 14). A post-split increase in absolute deviation indicates a deviation further from zero (becoming less efficient), while a post-split decrease in absolute deviation indicates a deviation closer to zero (becoming more efficient).

On day 1, absolute deviation decreased by 0.064% for ETF splits and decreased by 0.021% for reverse splits, indicating both splits and reverse splits resulted in deviations from NAV closer to zero and more efficient tracking. For traditional splits, absolute deviation from NAV appeared to increase in the days surrounding the split, then decrease in the longer-term (Figure 15). Reverse splits appeared to be more consistent in their deviation from NAV (Figure 16). For the most part, neither splits nor reverse splits resulted in statistically significant differences in absolute deviation from NAV (tracking efficiency) post-split (Table 5). Figures 15 and 16 depict the deviation from NAV in the 90 days leading up to and the 90 days following the splits and reverse splits.

Figure 13

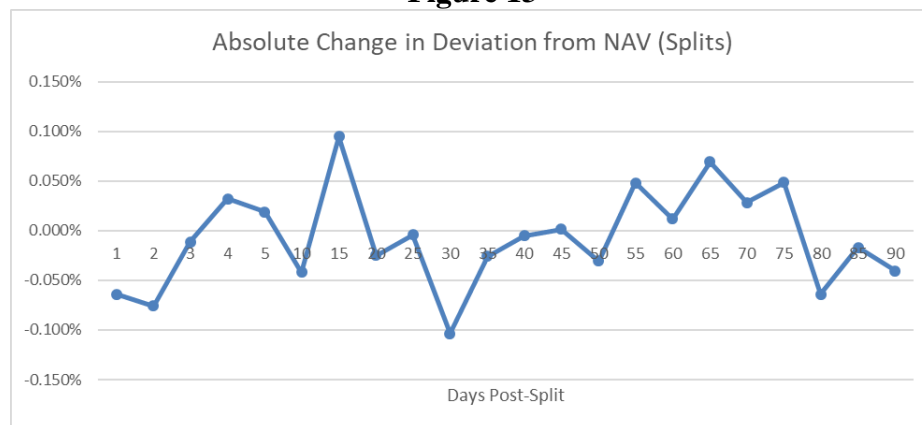


Figure 14

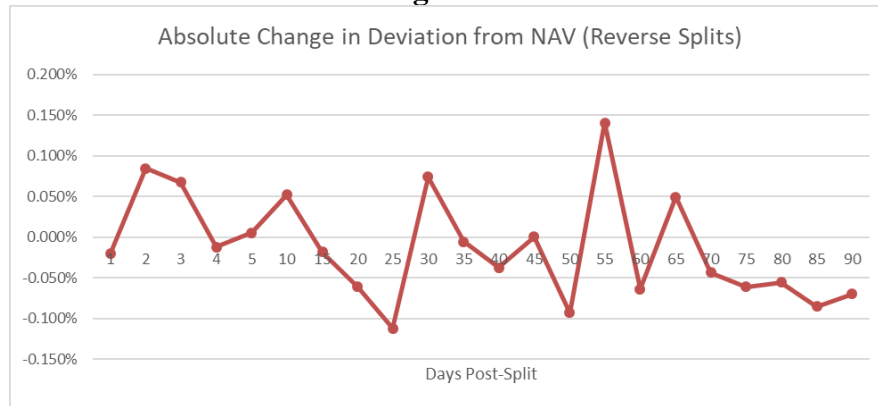


Figure 15

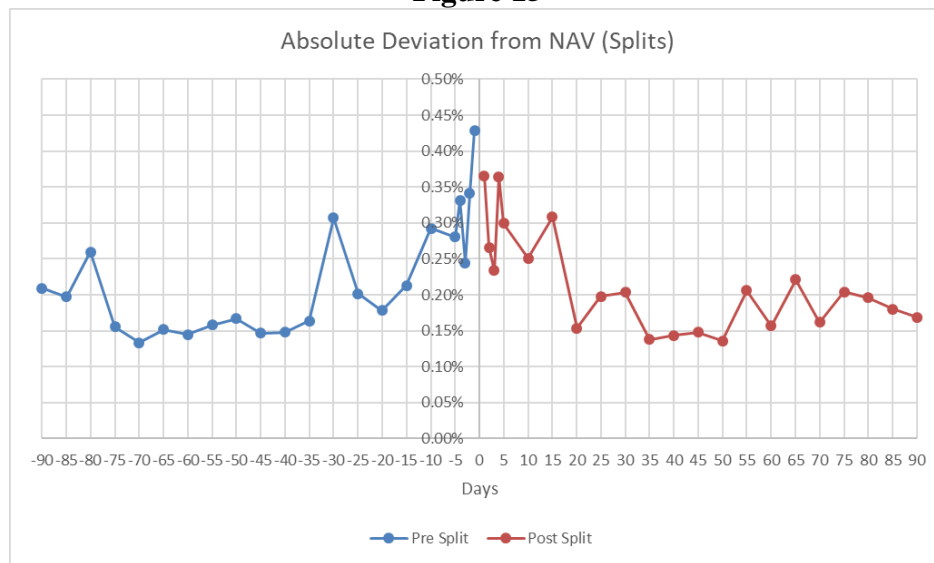
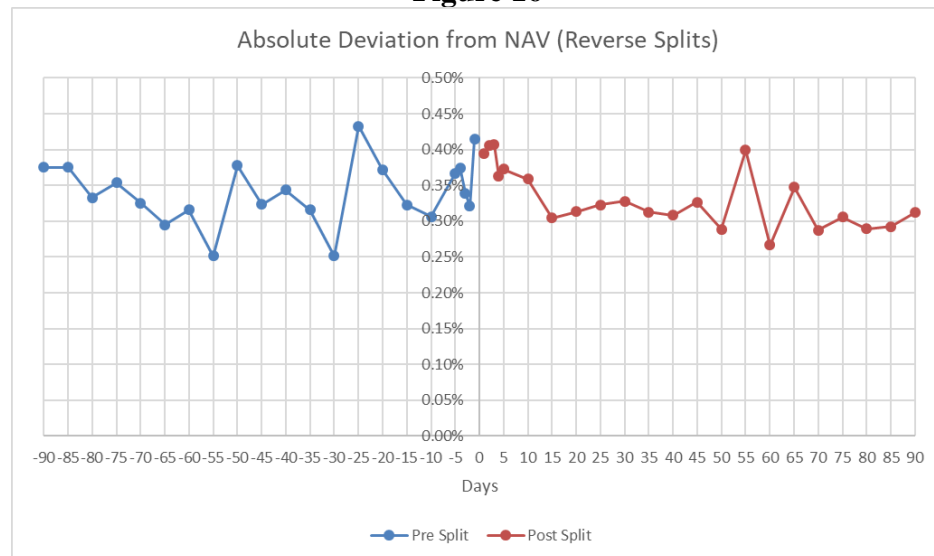


Figure 16



Summary of Results

Overall, ETF splits tended not to result in statistically significant differences in post-split trading volumes, while reverse splits did tend to result in statistically significant differences in post-split trading volumes. This held no matter how the data was sorted, whether by year, split ratio, or volume. The data shows significant evidence consistent with failing to reject the hypothesis that for traditional ETF splits, trading volumes are the same post-split. For reverse splits, there is evidence to reject the hypothesis that trading volumes are the same post-split.

Neither traditional ETF splits nor reverse splits tended to result in statistically significant differences in post-split deviation from NAV or tracking efficiency. The data shows evidence consistent with failing to reject the hypothesis that for both splits and reverse splits, deviations from NAV and tracking efficiency are the same post-split.

Discussion

In theory, trading activity should not change significantly following splits or reverse splits, as underlying fundamentals do not change. However, the results presented suggest that nominal ETF prices may influence investors. The effects could be caused by investor preference for stocks at a certain price level, by increased attention paid to stocks due to the attention-grabbing stock split, or by some other explanation, and is left to future research.

Trading Volumes

Previous research has shown differing results on the impact that stock splits have on trading volumes, a measure of liquidity. Mohanty and Moon (2007) showed that trading volumes and liquidity increase following a split, while Rudnicki (2012) found that trading volumes and liquidity decreased following a split. Taking this research and applying it to ETFs can determine whether ETFs behave similar to stocks following a split. Changes in liquidity are important to investors, and many investors consider liquidity before making an investment decision. Liquidity impacts transaction costs, like bid-ask spreads, and investors' ability to get in and out of investments.

On a broad level, the data collected here supports the assumption that splits and reverse splits impact trading volumes, and therefore liquidity. ETFs that underwent a split, on average, tended to see an increase in trading volume, and ETFs that underwent a reverse split saw a dramatic increase in trading volume. This implies that liquidity for ETFs does increase following both a split and reverse split. For splits, it appears that ETFs with lower initial volumes may have been largely responsible for the initial volume increase. Other than this, no matter how the data was sorted, there did not appear to be many consistent patterns that emerged. The same can be said for reverse splits, which resulted in highly positive impacts on trading volumes following

the reverse split no matter how the data was sorted. It should be noted that while both ETF splits and reverse splits tended to result in increased trading volumes post-split, this does not mean they behaved the same. Splits saw few statistically significant differences and much less impact on trading volumes compared to reverse splits. While reverse splits saw increased trading volumes post-split no matter how the data was sorted, traditional splits saw some periods of time with a decrease in trading volumes post-split. What is surprising is that both splits and reverse splits tended to result in an increase in trading volume and, therefore, liquidity. It would have made complete sense for splits and reverse splits to see opposite effects post-split. Both splits and reverse splits, but more so reverse splits, had their average change in volumes influenced by a high number of very large positive changes. This could have skewed the average changes in volumes post-split, as the highest possible negative change is -100% because trading volumes cannot be negative, whereas the highest possible positive change is positive infinity.

One way to interpret the results is to focus on the effect that splits and reverse splits had on nominal share price. Much research has been conducted on the impact that nominal share price has on investor behavior, and it has been shown that nominal shares prices do impact investor behavior. Stock splits are a good way to test this, especially with ETFs, as the underlying assets do not change, only the price and shares outstanding change in accordance with the size of the split. The results presented suggest that nominal price may influence investors in terms of liquidity. As seen in Figures 5 and 6, it appears that ETFs with more drastic split ratios initially and in the longer-term see the biggest changes in volumes post-split, consistent with nominal share prices influencing behavior. The more drastic the split, the bigger the change in nominal share price, so seeing bigger initial shifts in volumes post-split for more extreme splits suggests that larger changes in prices influence investors more than smaller

changes. Svedsater et al. (2007) found that investors were more willing to trade a stock after a split, which is consistent with the findings in this research. However, the same study found that investors are less likely to trade after a reverse split, which is not consistent with the findings of this research. Further, numerous studies have shown that investors view low priced stocks as having more potential upside than high priced stocks. This theory is one potential answer to why trading volumes of ETFs were found to increase following a split. If investors view the post-split, lower price ETFs as having a higher chance to achieve outsized returns, investors may be more willing to purchase the ETFs, thus increasing volumes. However, this theory does not explain why reverse splits, in which the nominal price increases, lead to increased trading volumes as well. If this theory held for reverse splits, then trading volume should have fallen post-split for reverse splits. The findings are consistent with nominal share price influencing investor behavior.

Another theory as to why stocks undergo splits and reverse splits is to keep the share price in a desired range that investors prefer. While not done in this research, it may be valuable to look at the price the ETFs are splitting to and compare this to post-split trading volumes to determine if ETFs in a certain price range trade more frequently. Companies that manage ETFs may actively manage share prices depending on how investors react to different prices. The increase in volume post-split and post-reverse split adheres to the idea that companies undergo splits to make nominal prices more appealing to investors.

Deviation From NAV

ETF mispricing is very uncommon due to arbitrageurs who correct mispricing very quickly. For the most part, the results presented in this research support this idea, with the magnitude of change in deviation from NAV showing almost no statistically significant

differences in deviations from NAV post-split for both splits and reverse splits. In both cases, moving further away from the split date results in what appear to be random fluctuations for magnitude of deviation from NAV, suggesting that ETFs are mostly priced efficiently pre- and post-split. However, splits appear to have a slight increase in fluctuations in deviation from NAV in the 35 days pre-split and post-split, and peak on the day of the split. If markets are completely efficient, there should be only random fluctuations in deviation from NAV and very little mispricing of ETFs. The increase in deviation from NAV in the days surrounding the split, and thus an increase in mispricing, should not be present in an efficient market and supports the idea of irrational investor behavior and inefficiencies in the market.

Using the absolute value of pre-split and post-split deviations from NAV to measure tracking efficiency, the results also show almost exclusively no statistically significant differences in absolute deviation, and thus tracking efficiency, post-split. There appear to be random fluctuations in the change in absolute deviation as time passes for both splits and reverse splits. However, for splits, absolute deviation from NAV appears to increase around the time of the split. The increase in absolute deviations surrounding the split could potentially signal slight mispricing surrounding the split, and therefore irrational investor behavior. Reverse splits saw a drastic increase in volume post-split, so if anything, one would expect tracking efficiency to increase. Looking further into how splits are related to short-term mispricing of ETFs may provide additional insight on the impact ETF splits have on nominal pricing.

Many studies have shown that ETFs track their underlying assets very closely and that only very slight deviations from NAV exist. Ackert and Tian (2008) suggest that a higher liquidity of ETFs is associated with a lower premium to NAV, or a lower deviation from NAV. As discussed above, both ETF splits and reverse splits on average saw an increase in trading

volumes. This would suggest that post-split, ETFs may see a lower deviation from NAV, or more efficient tracking, as a result of the increased trading and liquidity. However, this was not the case. While changes in deviations from NAV are present post-split, they appear in a random manner that is unassociated with changes in liquidity. This may suggest the ETFs were already priced efficiently, so increasing liquidity would not have much of an impact.

Implications/Future Research

Investors do not always act rationally, and investor behavior can be difficult to predict. This research supports that theory, as it shows that ETF splits and reverse splits have the ability to impact trading volumes, and thus liquidity. It also shows that ETFs can potentially take it upon themselves to increase liquidity by splitting their ETFs. It is possible that, by splitting to a lower price, ETFs can take advantage of a high price premium investors place on low priced stocks. This could cause low priced ETFs to trade at a premium relative to high priced ETFs, although this may not hold because, unlike stocks, ETFs track a basket of underlying goods. Further research could be conducted to determine the impact splits and reverse splits have on nominal price. Additionally, it would be interesting to test if, as found with stocks by Birru and Wang (2016), investors view low priced ETFs as having more upside potential than high priced ETFs. If investors view the post-split, lower price ETFs as having a higher chance to achieve outsized returns, investors may be more willing to purchase the ETFs, which may drive up price.

Similarly, looking at how returns change following splits and reverse splits could offer further understanding to irrational investor behavior and how nominal price influences behavior. ETFs should not see any change in returns, as price is tied to underlying assets and splits do not change these underlying assets. It may also be possible to measure how the number of small trades and individual investors change following a split or reverse split, as this may be an explanation for an increase in volume post-split. An increase in the number of individual investors that start trading the ETF may cause an increase in noise trading, perhaps due to the increased attention to the ETF brought about by the split itself.

After a number of years, it may be insightful to compare the number of ETF splits and reverse splits to the “Low-Price Premium” variable, found by Baker, Greenwood, and Wurgler

(2009), which measures demand for low-priced stocks. This would provide further information on whether companies respond to increased demand for low priced stocks by increasing the number of splits. By comparing post-split volumes to the “Low-Price Premium” variable, ETF splits could also be used to determine whether there is increased liquidity following a split in periods of high demand for low priced stocks.

The results provided show reverse splits resulted in drastic increases in volumes for ETFs. It is not initially clear why this is the case, and why the results were so different for splits. Collecting further data on the reverse splits could provide some answers. For example, perhaps the pre-split prices were extremely low, and the reverse splits resulted in share prices investors were more comfortable trading.

This research also provides some evidence that ETFs demonstrate an increase in mispricing in the days surrounding the split, which allows for increased arbitrage opportunities if investors can take advantage of the mispricing. It may be valuable to collect intraday deviations from NAV on the day of the split to get a better idea how efficiently price tracks the NAV throughout the day, not just at close.

In summary, this research provides a look into how ETF splits and reverse splits impact trading volumes, a proxy for liquidity, and how deviations from NAV and tracking efficiency change following a split or reverse split. The tests performed in this research may benefit from a longer time horizon, as the tests for significance were conducted with a relatively small sample size. Having more data points would lead to more certainty in what is occurring following splits and reverse splits. The findings in this research provide a foundation for future research considering ETF behavior. As ETFs continue to grow in popularity, it will be interesting to see how investor behavior surrounding ETFs adapts.

Appendix

Table 1

		Number of Splits																					
Days Pre- and Post Split		1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
Year	All	92	89	86	86	84	83	80	79	79	79	79	73	73	73	73	73	72	72	72	72	72	72
	2016	23	22	22	22	22	22	22	21	21	21	21	21	21	21	21	21	20	20	20	20	20	20
	2015	37	35	32	32	30	30	29	29	29	29	29	28	28	28	28	28	28	28	28	28	28	28
	2014	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	
	2013	11	11	11	11	11	10	10	10	10	10	10	9	9	9	9	9	9	9	9	9	9	
	2012	7	7	7	7	7	7	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	
	2011	7	7	7	7	7	7	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	
	2010	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	
Split Ratio	2	43	42	41	41	41	40	38	38	38	38	38	37	37	37	37	37	37	37	37	37	37	37
	3	16	16	16	16	16	16	16	16	16	16	16	12	12	12	12	12	11	11	11	11	11	11
	4	29	27	25	25	23	23	22	22	22	22	22	21	21	21	21	21	21	21	21	21	21	21
Volume on Day 1	>1000000	15	15	15	15	15	15	15	15	15	15	15	14	14	14	14	14	14	14	14	14	14	14
	100000-1000000	27	27	27	27	27	27	27	27	27	27	27	25	25	25	25	25	25	25	25	25	25	25
	<100000	50	47	44	44	42	41	38	37	37	37	37	34	34	34	34	34	33	33	33	33	33	33

Table 1 provides information for how many ETF splits were used to measure changes in trading volumes post-split. The information is further sorted by characteristic. For example, to measure the change in volume on the fifth day post-split for ETFs that had a split ratio of 4, 23 splits were used.

Table 2

		Number of Reverse Splits																					
Days Pre- and Post Split		1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
Year	All	152	151	150	149	149	146	143	141	141	140	138	137	135	134	133	132	132	132	132	132	132	132
	2016	29	29	29	28	28	28	28	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27
	2015	24	24	24	24	24	23	23	23	23	23	22	22	22	22	21	21	21	21	21	21	21	21
	2014	22	22	22	22	22	21	20	19	19	19	19	18	16	15	15	15	15	15	15	15	15	15
	2013	25	25	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
	2012	17	16	16	16	16	16	15	14	14	14	13	12	12	12	12	12	12	12	12	12	12	12
	2011	22	22	22	22	22	22	21	21	21	21	21	21	21	21	21	20	20	20	20	20	20	20
	2010	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Split Ratio	<.2	15	15	15	15	15	15	15	15	15	15	14	14	14	14	14	14	14	14	14	14	14	14
	0.2	35	35	35	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
	0.25	71	70	70	70	70	68	65	64	64	63	62	61	59	58	57	57	57	57	57	57	57	57
	0.3333	15	15	14	14	14	14	14	13	13	13	13	13	13	13	13	12	12	12	12	12	12	12
	0.5	16	16	16	16	16	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Volume on Day 1	>1000000	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22
	100000-1000000	49	49	49	49	49	49	49	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48
	<100000	81	80	79	78	78	75	72	71	71	70	68	67	65	64	63	62	62	62	62	62	62	62

Table 2 provides information for how many ETF reverse splits were used to measure changes in trading volumes post-split. The information is further sorted by characteristic. For example, to measure the change in volume on the fifth day post-split for ETFs that had a split ratio of 0.25, 70 splits were used.

Table 3

T-test Significance Results for Change in Volumes																							
		Splits																					
Day	1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	
Year																							
All	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
2016	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
2015	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2014																							
2013	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
2012	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
2011	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
2010	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Split Ratio																							
2	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
3	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
4	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Volume on Day 1																							
>1000000	No	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
100000-1000000	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
<100000	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 3 shows the results of t-tests performed for ETF splits to test for statistical significance in post-split volumes. Tests that show “Yes” imply there is a statistically significant difference in pre-split and post-split volumes, while tests that show “No” imply there is not a statistically significant difference in pre-split and post-split volumes. For example, for all splits, the average volume 3 days after the split is not significantly different compared to the average volume 3 days prior to the split. However, for all splits, the average volume 4 days after the split *is* significantly different compared to the average volume 4 days prior to the split. (2014 omitted due to small sample size)

Table 4

T-test Significance Results for Change in Volumes																							
		Reverse Splits																					
	Day	1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
By Year																							
	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2016	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2015	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2014	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2013	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2012	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2011	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
	2010	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Split Ratio																							
	<.2	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.3333	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No
Volume on Day 1																							
	>1000000	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	100000-1000000	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	<100000	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 is the same as Table 3, except Table 4 displays the results of t-tests for reverse splits instead of splits.

Table 5

Deviation From NAV for All Splits																						
Days	1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
Change in Magnitude of Deviation?	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Change in Tracking Efficiency?	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	Yes	No	No	No	No	No	No
Deviation From NAV for All Reverse Splits																						
Days	1	2	3	4	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90
Change in Magnitude of Deviation?	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	Yes	No	No	No	No	No	No
Change in Tracking Efficiency?	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table 5 shows the results of the t-test for significance regarding change in magnitude of deviation from NAV and change in tracking efficiency for each time period (as measured using absolute values of deviation). For example, for reverse splits, there is a statistically significant difference in the change in magnitude of deviation on the 60th day post-split compared to the 60th day pre-split.

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